Application of Artificial Neural Networks in wave height prediction in the Persian Gulf

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Abstract

Accurate wave prediction and supplement is an important task in determining constructions and management of coastal structures. However, determination of wave characteristics is of particular importance. In the present study, the artificial intelligence methodology of neural networks is used to forecast the waves based on learning the characteristics of observed waves, rather than the use of the wind information. The measurements from a single station at Bushehr, North coast of the Persian Gulf, for the period July 2007 - August 2007 were used to train and to validate the employed neural networks. The results obtained show the feasibility of the neural wave characteristics forecasts for 1 and 2 h in terms of the correlation coefficient (0.78–0.9), root mean square error (.03-.07) and scatter index (0.2–0.4). Therefore, the proposed methodology could be successfully used for site-specific forecasts. It is shown that the data produced with the approach developed in this work have statistical properties very close to the properties of the measurements, thus proving that this approach can be used as a reliable tool for wind wave forecasting in coastal areas, complementary to spectral and numerical wave models.

Keywords

Prediction; Significant Waves Height; Neural Networks; Persian Gulf

Introduction

Estimation of ocean wave parameters is useful for design of harbor, coastal structures, offshore structures, defense purposes, coastal erosion and wave energy estimation. Waves are mostly generated by wind and have irregular characteristics, caused by the irregular nature of wind. Due to this irregular nature an accurate approach for predicting wave is a difficult task. In order to overcome problems , some statistical method is employed and ANN (artificial neural network) is one of the most effective which have proven their usefulness in oceanographic studysuch as simulation of waves. However, the artificial neural network (ANN) method is not defined as a specific equation form, it has an advantage over the empirical model as it can continuously retrain the new recorded data and adapt to update data. In the past decades the ANN approach, which is a non-linear black box model, was applied for wave and tide predictions. Some of these applications are as follows: Makarynska and Makarynskyy (2008) predicted sea-level variation at the Cocos Islands with artificial neural networks with high accuracy. Haung et al. (2003) used ANN techniques to predict coastal water level along the South shore of Long Island, New York. Liang (2008) applied ANN for prediction of tidal level including strong meteorological effects. Gunaydin (2008) worked in the estimation of monthly mean significant wave heights by using ANN and regression method.

Srtructue Of ANN

This work back-propagation neural network(BPN) is used which consists of three layers. The first one is the input layer and the last one is the output layer and the layers between the input and output is called the hidden layer (see Fig. 1). Each layer is made up of several neurons and the layers are interconnected by sets of corresponding weights. There is no definite theoretical background for determination of ANN's architecture (number of neurons and pattern of their interconnections) most suitable for each particular case study. It depends on difficulty of problem and is found by trial and error. Huang and Foo (2002) suggested an empirical expression for neurons in hidden layer:

$$h=2n+1 \quad (1)$$

where n is the number of input neurons and h is the number of hidden neurons. The input layer neurons receive initial input information, after that outputs are obtained using various transfer functions. We have used past recorded data as inputs and Hs will be predicted in the output layer.

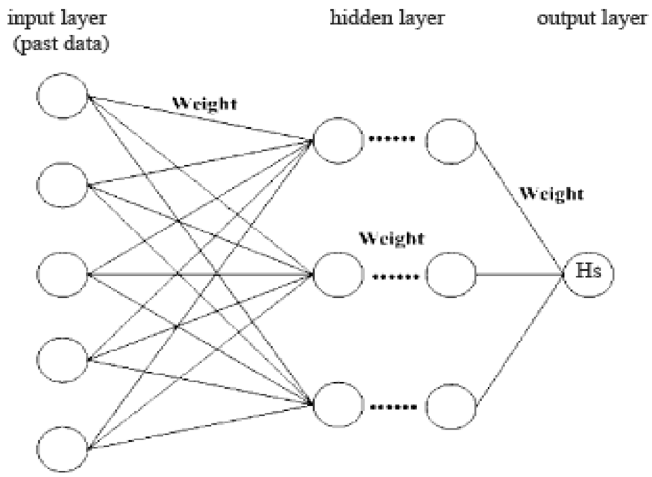

FIG. 1 A TYPICAL ANN USED

Data Collection

In the application of ANN , two data sets are required. The first set for training task and the second one for evaluating the performance of ANN. The data from 'OCEANOR' buoy, which is moored offshore of Bushehr (29º 2' 12'' N, 50º 32'10'' E) (Fig. 2) and is maintained by the Port and Maritime Organization which were used to train and test the ANNs employed. The hourly values of the Hs for the period from July 8, 2007 to August 2, 2007 are available. This data set is divided into two independent parts. The first part (from July 8 to July 27) is used to train the corresponding neural networks, while the second part (July 28 to August 2) is served for validation purposes.

FIG. 2 LOCATION MAP OF THE BUOY STATION

Verification

The validation of the ANN's is performed in terms of some statistical parameters as follows: the correlation coefficient R, root mean square error RMSE and scatter index SI computed as:

$$R = \frac{\sum_{i=1}^{N}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{N}(X_i-\bar{X})^2 \sum_{i=1}^{N}(Y_i-\bar{Y})^2}} \tag{2}$$

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(Y_i-X_i)^2}{N}} \tag{3}$$

$$\text{SI}=\frac{RMSE}{X} \tag{4}$$

Where X_i is observed Hs value at the ith time step, Y_i is the simulated Hs value at the same moment of time, N is the number of time increments, $\bar{X}$ is the mean value of observations, and $\bar{Y}$ is the mean value of simulations.

Results and Discussion

It was assumed that an hourly wave history contained all the necessary information to predict the Hs one (+1 h), two (+2 h), three (+3 h) and four (+4 h) time steps ahead. The resilient back propagation training algorithm was implemented to train all of these nets. The number of training epochs in each simulation was 1000. The nets used at the beginning with 8 input nodes, 17 processing neurons (see Eq. (1)) and 1 output neuron (hereafter referred to as (8,17,1) and likewise for other nets) work as follows. Each input layer of 8 nodes transfers the initial information to 17 hidden processing units, which further fire the result of simulation to the interested user through the only output neuron. The result of ANN (8,17,1) model is shown in Fig. 3. An analysis of the statistics in Fig. 3 demonstrates that the net with 8 neurons in the input layer has not high accuracy. As mentioned before for improving the results , the ANN's structures must be changed. In this paper we use the simplest (but widely effective) case when the number of input neuron is variable. At the next time 5 input neurons is assumed to the input layer and Hs is simulated for different time step. When short prediction intervals of one and two hours were concerned, the Hs was forecasted by this net with high accuracy. The RMSE were less than or equal to 0.06 m, the coefficients of correlation were higher than or equal to 0.78 and the scatter indexes of these forecasts were less than or equal to 0.37. The predictions of the Hs for 3 h were less reliable, while the predictions with leading time of 4 h exhibited neither a reliable correlation pattern nor reasonable values of RMSE and SI (table. 1). Fig. 4 compares between measured and predicted value for 1h time step.

In order to access the role of the input neuron , some more experiments were performed. The results of ANN (4,9,1) and ANN (3,7,1) model are detailed in table1. When short prediction intervals of 1 and 2 h were concerned, both of them had high accuracy. But the predictions for 3 and 4 h were less reliable particularly in ANN (3,7,1) model for 4 time steps. A comparison between measured and predicted value of Hs is shown in Fig.5 for ANN (4,9,1). The nets with 1 and 2 neurons in input layer were skipped out because of their lowest performance in the prediction of Hs.

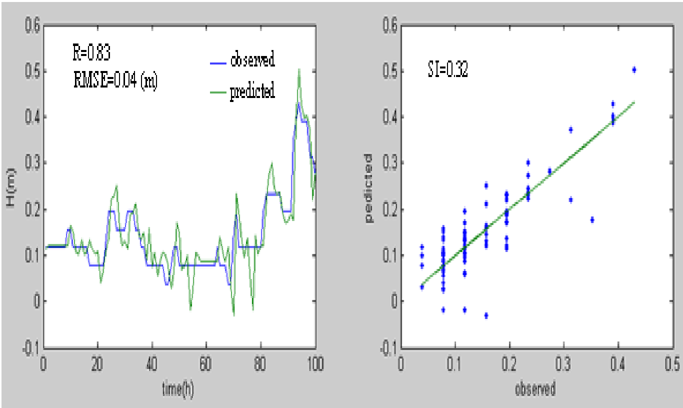

FIG. 3 COMPARISON BETWEEN MEASURED VALUE AND PREDICTED VALUE BY ANN (8,17,1) FOR (1H AHEAD)

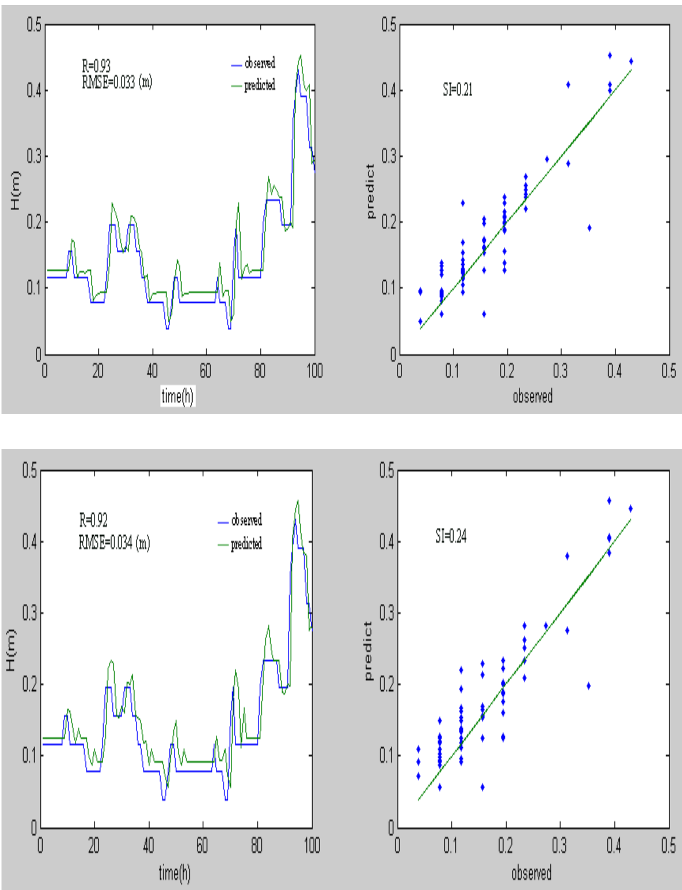

FIG. 4 COMPARISON BETWEEN MEASURED VALUE AND PREDICTED VALUE BY ANN (4,9,1) FOR (1H AHEAD)

TABLE 1 VALIDATION STATISTICAL OBTAINED FROM EACH ANN WITH DIFFERENT LEAD TIME

ANN model	Time step(h)	R	RMSI(m)	SI
ANN(5,11,1)	1	0.93	0.033	0.21
ANN(5,11,1)	2	0.78	0.06	0.37
ANN(5,11,1)	3	0.75	0.07	0.41
ANN(5,11,1)	4	0.50	0.1	0.50
ANN(4,9,1)	1	0.92	0.034	0.24
ANN(4,9,1)	2	0.74	0.079	0.4
ANN(4,9,1)	3	0.72	0.082	0.45
ANN(4,9,1)	4	0.55	0.13	0.9
ANN(3,7,1)	1	0.93	0.033	0.26
ANN(3,7,1)	2	0.83	0.055	0.33
ANN(3,7,1)	3	0.68	0.08	0.45
ANN(3,7,1)	4	0.29	0.17	0.65

Concluding Remarks

The technique of artificial neural networks was used to predict significant wave heights with warning times of 1, 2, 3 and 4h. The simulations were compared to time series of this wave parameter estimated off the coast of Bushehr. The neural forecasts generally follow the rising and falling trends present in the observations. Different levels of accuracy in terms of the root mean square error, correlation coefficient and scatter index were achieved. The ANN's performance changed according to the lead-time and ANN's structure. The wave parameters were better simulated for shorter lead times (1 and 2 h) than for longer prediction intervals (3 and 4 h).

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